Introduction

Importation des library et des donnees

```
# library Importation
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from geopy.geocoders import Nominatim
import cachetools
from sklearn.impute import SimpleImputer
from sklearn.tree import DecisionTreeClassifier, plot_tree, export_text
# Random Forest
from sklearn.ensemble import RandomForestClassifier
# Evaluation metrices
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score, recall_score, f1_score, classification_report, roc_curve,
from sklearn.ensemble import RandomForestClassifier
import warnings
warnings.filterwarnings('ignore')
# Data frames reading
# Train
df_train = pd.read_csv("/content/train_Insurance.csv")
display (df_train)
# Test
df_test = pd.read_csv("/content/test_Insurance.csv")
display (df_test)
```

| r | | _ |
|---|---|---|
| - | → | 4 |
| | | |

| | Customer Id | YearOfObservation | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Bu |
|------|----------------|-------------------|----------------|-------------|------------------|-----------------|--------|------------|-----------------------|----|
| 0 | H13501 | 2012 | 1.0 | 1 | N | V | V | U | 1240.0 | 1 |
| 1 | H14962 | 2012 | 1.0 | 0 | N | V | V | U | 900.0 | |
| 2 | H17755 | 2013 | 1.0 | 1 | V | N | 0 | R | 4984.0 | |
| 3 | H13369 | 2016 | 0.5 | 0 | N | V | V | U | 600.0 | 1 |
| 4 | H12988 | 2012 | 1.0 | 0 | N | V | V | U | 900.0 | |
| | | | | | | | | | | |
| 5007 | H13682 | 2013 | 1.0 | 0 | N | V | V | U | 550.0 | |
| 5008 | H18342 | 2012 | 0.5 | 0 | V | N | 0 | R | 1000.0 | |
| 5009 | H16892 | 2015 | 1.0 | 1 | V | N | 0 | R | 480.0 | |
| 5010 | H18805 | 2012 | 0.5 | 0 | V | N | 0 | R | 536.0 | |
| 5011 | H18228 | 2013 | 1.0 | 1 | V | V | V | U | NaN | 1 |

5012 rows × 13 columns

| | Customer Id | YearOfObservation | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Bu |
|------|----------------|-------------------|----------------|-------------|------------------|-----------------|--------|------------|-----------------------|----|
| 0 | H3733 | 2013 | 1.0 | 0 | V | V | V | U | 3760.0 | |
| 1 | H16909 | 2015 | 1.0 | 0 | V | N | 0 | R | 1452.0 | |
| 2 | H16867 | 2013 | 1.0 | 1 | V | N | 0 | R | 1944.0 | |
| 3 | H14813 | 2015 | 1.0 | 0 | N | V | V | U | 2270.0 | |
| 4 | H3728 | 2016 | 0.5 | 0 | V | N | 0 | R | 2976.0 | |
| | | | | | | | | | | |
| 2142 | H19924 | 2016 | 0.5 | 1 | V | N | 0 | R | 862.0 | 1 |
| 2143 | H17249 | 2012 | 1.0 | 0 | V | V | V | U | NaN | |
| 2144 | H18804 | 2014 | 1.0 | 0 | V | N | 0 | R | 730.0 | |
| 2145 | H12650 | 2014 | 1.0 | 1 | N | V | V | U | 568.0 | |
| 2146 | H13879 | 2013 | 0.5 | 0 | N | V | V | U | 730.0 | |

2147 rows × 13 columns

```
#fonction qui seront etre utilisé plus tard
```

```
# Fonction pour le traitement des valeur manquantes
def traitement_des_valeurs_manquantes(df,NomDuColone):
 mf_imputer = SimpleImputer(missing_values=np.nan, strategy='most_frequent')
  df[NomDuColone] = mf_imputer.fit_transform(df[[NomDuColone]])
 return df
# Fonction pourt elimination des outliers
{\tt def treatment\_des\_outliers(df,feature):}
  Q1,Q3=np.percentile(df[feature],[25,75])
  IQR=Q3-Q1
  lower\_limit=max(Q1 - 1.5 * IQR, df[feature].min()+100)
  \# Lower_limit is -2125 building dimension can t be negatif nor close to 0
  upper_limit=Q3+1.5*IQR
  df[feature]=np.where(df[feature]>=upper_limit,
  upper_limit, np.where(df[feature]<=lower_limit,</pre>
  lower_limit,df[feature]))
  return df
```

Analyse des Donnees

| | 0 |
|---------------------------|---------|
| Customer Id | object |
| YearOfObservation | int64 |
| Insured_Period | float64 |
| Residential | int64 |
| Building_Painted | object |
| Building_Fenced | object |
| Garden | object |
| Settlement | object |
| Building Dimension | float64 |
| Building_Type | object |
| NumberOfWindows | object |
| Geo_Code | object |
| Claim | object |
| dtype: object | |

dtype: object

| 0 |
|---------|
| object |
| int64 |
| float64 |
| int64 |
| object |
| object |
| object |
| object |
| float64 |
| object |
| object |
| object |
| object |
| |

dtype: object

#EDA : Statistique descriptif

display(df_train.describe(include='all')) # (all) Pour les colonnes categorielle aussi
display(df_test.describe(include='all')) # (all) Pour les colonnes categorielle aussi

| | Customer Id | YearOfObservation | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension |
|---|--------------------------------------|--|--|--|---|---|---|---|--|
| count | 5012 | 5012.000000 | 5012.000000 | 5012.000000 | 5012 | 5012 | 5008 | 5012 | 4935.000000 |
| unique | 5012 | NaN | NaN | NaN | 2 | 2 | 2 | 2 | Nah |
| top | H13501 | NaN | NaN | NaN | V | N | 0 | R | NaN |
| freq | 1 | NaN | NaN | NaN | 3763 | 2535 | 2532 | 2537 | NaN |
| mean | NaN | 2013.660215 | 0.869713 | 0.301077 | NaN | NaN | NaN | NaN | 1876.898683 |
| std | NaN | 1.383134 | 0.219496 | 0.458772 | NaN | NaN | NaN | NaN | 2267.277397 |
| min | NaN | 2012.000000 | 0.500000 | 0.000000 | NaN | NaN | NaN | NaN | 1.000000 |
| 25% | NaN | 2012.000000 | 0.500000 | 0.000000 | NaN | NaN | NaN | NaN | 520.000000 |
| 50% | NaN | 2013.000000 | 1.000000 | 0.000000 | NaN | NaN | NaN | NaN | 1067.000000 |
| 75% | NaN | 2015.000000 | 1.000000 | 1.000000 | NaN | NaN | NaN | NaN | 2280.000000 |
| max | NaN | 2016.000000 | 1.000000 | 1.000000 | NaN | NaN | NaN | NaN | 20840.000000 |
| | | | | | | | | | |
| | Customer Id | YearOfObservation | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension |
| count | | YearOfObservation 2147.000000 | Insured_Period 2147.000000 | Residential 2147.000000 | Building_Painted 2147 | Building_Fenced 2147 | Garden 2144 | Settlement 2147 | |
| count | Id | | | | | | | | Dimension |
| | 2147 | 2147.000000 | 2147.000000 | 2147.000000 | 2147 | 2147 | 2144 | 2147 | 2118.000000 |
| unique | 2147 2147 | 2147.000000 NaN | 2147.000000 NaN | 2147.000000 NaN | 2147 | 2147 | 2144 | 2147 | 2118.000000 NaN |
| unique top | 2147 2147 H3733 | 2147.000000 NaN NaN | 2147.000000 NaN NaN | 2147.000000 NaN NaN | 2147 2 V | 2147 2 V | 2144 2 V | 2147 2 U | 2118.00000(Nah Nah |
| unique top freq | 2147 2147 H3733 | 2147.000000 NaN NaN NaN | 2147.000000 NaN NaN NaN | 2147.000000 NaN NaN NaN | 2147 2 V 1619 | 2147 2 V 1074 | 2144 2 V 1074 | 2147 2 U 1074 | Dimension 2118.000000 Nah Nah Nah |
| unique top freq mean | 1d 2147 2147 H3733 1 NaN | 2147.000000 NaN NaN NaN 2013.691197 | 2147.000000 NaN NaN NaN 0.876805 | 2147.000000 NaN NaN NaN 0.315789 | 2147 2 V 1619 NaN | 2147 2 V 1074 NaN | 2144 2 V 1074 NaN | 2147 2 U 1074 NaN | Dimension 2118.00000(Nah Nah Nah 1899.70018(|
| unique top freq mean std | 1d 2147 2147 H3733 1 NaN NaN | 2147.000000 NaN NaN NaN 2013.691197 1.385631 | 2147.000000 NaN NaN NaN 0.876805 0.215504 | 2147.000000 NaN NaN NaN 0.315789 0.464938 | 2147 2 V 1619 NaN NaN | 2147 2 V 1074 NaN NaN | 2144 2 V 1074 NaN | 2147 2 U 1074 NaN NaN | Dimension 2118.000000 Nah Nah Nah 1899.700188 2304.300053 |
| unique top freq mean std min | 1d 2147 2147 H3733 1 NaN NaN | 2147.000000 NaN NaN NaN 2013.691197 1.385631 2012.000000 | 2147.000000 NaN NaN NaN 0.876805 0.215504 0.500000 | 2147.000000 NaN NaN NaN 0.315789 0.464938 0.000000 | 2147 2 V 1619 NaN NaN | 2147 2 V 1074 NaN NaN | 2144 2 V 1074 NaN NaN | 2147 2 U 1074 NaN NaN | Dimension 2118.00000(Nah Nah Nah 1899.70018(2304.30005(10.00000() |
| unique top freq mean std min 25% | 1d 2147 2147 H3733 1 NaN NaN NaN NaN | 2147.000000 NaN NaN NaN 2013.691197 1.385631 2012.000000 | 2147.000000 NaN NaN NaN 0.876805 0.215504 0.500000 1.000000 | 2147.000000 NaN NaN NaN 0.315789 0.464938 0.0000000 0.0000000 | 2147 2 V 1619 NaN NaN NaN | 2147 2 V 1074 NaN NaN NaN | 2144 2 V 1074 NaN NaN NaN | 2147 2 U 1074 NaN NaN NaN | Dimension 2118.000000 Nah Nah Nah 1899.700188 2304.300053 10.0000000 535.5000000 |

DF Info

display(df_train.info())
display(df_test.info())

<class 'pandas.core.frame.DataFrame'>
 RangeIndex: 5012 entries, 0 to 5011 Data columns (total 13 columns):

| # | Column | Non-Null Count | Dtype |
|---------|--------------------|----------------|---------|
| | | | |
| 0 | Customer Id | 5012 non-null | object |
| 1 | YearOfObservation | 5012 non-null | int64 |
| 2 | Insured_Period | 5012 non-null | float64 |
| 3 | Residential | 5012 non-null | int64 |
| 4 | Building_Painted | 5012 non-null | object |
| 5 | Building_Fenced | 5012 non-null | object |
| 6 | Garden | 5008 non-null | object |
| 7 | Settlement | 5012 non-null | object |
| 8 | Building Dimension | 4935 non-null | float64 |
| 9 | Building_Type | 5012 non-null | object |
| 10 | NumberOfWindows | 5012 non-null | object |
| 11 | Geo_Code | 4939 non-null | object |
| 12 | Claim | 5012 non-null | object |
| diam'r. | (7 - + (4/2) : + (| 4/2) -1-1 | |

dtypes: float64(2), int64(2), object(9) memory usage: 509.2+ KB

None

cclass 'pandas.core.frame.DataFrame'>
RangeIndex: 2147 entries, 0 to 2146
Data columns (total 13 columns):

| # | Column | Non-Null Count | Dtype |
|------|----------------------|-----------------|---------|
| | | | |
| 0 | Customer Id | 2147 non-null | object |
| 1 | YearOfObservation | 2147 non-null | int64 |
| 2 | Insured_Period | 2147 non-null | float64 |
| 3 | Residential | 2147 non-null | int64 |
| 4 | Building_Painted | 2147 non-null | object |
| 5 | Building_Fenced | 2147 non-null | object |
| 6 | Garden | 2144 non-null | object |
| 7 | Settlement | 2147 non-null | object |
| 8 | Building Dimension | 2118 non-null | float64 |
| 9 | Building_Type | 2147 non-null | object |
| 10 | NumberOfWindows | 2147 non-null | object |
| 11 | Geo_Code | 2118 non-null | object |
| 12 | Claim | 2147 non-null | object |
| dtyp | es: float64(2), int6 | 4(2), object(9) | |

dtypes: float64(2), int64(2), object(9)
memory usage: 218.2+ KB

None

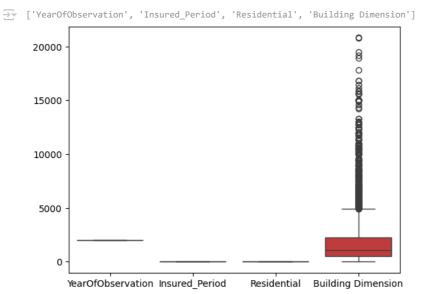
Detection des valeurs manquantes

display(df_train.isna().sum())
display(df_test.isna().sum())

```
0
         Customer Id
                          0
      YearOfObservation
                          0
       Insured_Period
         Residential
                          0
       Building_Painted
                          0
       Building_Fenced
                          0
           Garden
                          4
          Settlement
      Building Dimension 77
        Building_Type
      NumberOfWindows
                          0
          Geo_Code
                         73
            Claim
                          0
     dtype: int64
                          0
         Customer Id
                          0
      YearOfObservation
       Insured_Period
                          0
         Residential
                          0
       Building_Painted
                          0
       Building_Fenced
                          0
           Garden
         Settlement
                          0
      Building Dimension 29
        Building_Type
                          0
      NumberOfWindows
                          0
          Geo_Code
                         29
                          0
            Claim
     dtype: int64
#valeurs tres eloignées
# List of Numerical columns
numerical=list(df_train.select_dtypes(include="number"))
print(numerical)
```

Affichage des valeurs tres eloignées sns.boxplot(data=df_train[numerical])

plt.show()



Data Preprocessing (Feature By Feature)

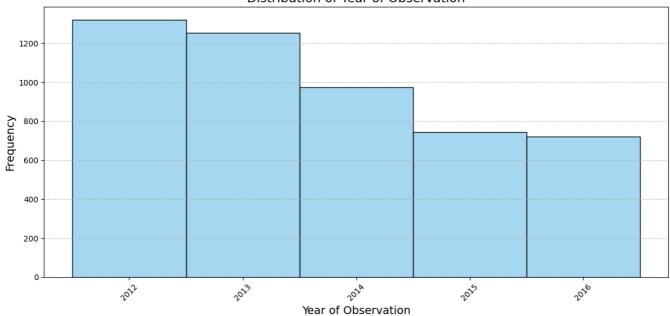
Customer Id Feature

```
# Analyse
print("Nomber of None Values = ",df_train['Customer Id'].isna().sum())
display(df_train["Customer Id"].describe())
print("Nomber of None Values = ",df test['Customer Id'].isna().sum())
display (df_test["Customer Id"].describe())
   Nomber of None Values = 0
           Customer Id
     count
    unique
                5012
               H13501
      top
     freq
    dtype: object
    Nomber of None Values = 0
           Customer Id
                2147
     count
                2147
    unique
      top
                H3733
     freq
    dtype: object
# Reduction de Dimension (Useless Feature)
df_train=df_train.drop(columns=["Customer Id"])
df_test=df_test.drop(columns=["Customer Id"])
# Verification
print(df_train.columns)
print(df_test.columns)
dtype='object')
    'Claim'],
         dtype='object')
```

YearOfObservation

```
# Analyse
print("Nomber of None Values = ",df_train['YearOfObservation'].isna().sum())
display(df_train["YearOfObservation"].describe())
print("Nomber of None Values = ",df test['YearOfObservation'].isna().sum())
display (df_test["YearOfObservation"].describe())
Nomber of None Values = 0
            YearOfObservation
                   5012.000000
     count
                   2013.660215
      mean
                      1.383134
       std
      min
                   2012.000000
      25%
                   2012.000000
      50%
                   2013.000000
      75%
                   2015 000000
                   2016.000000
      max
     dtype: float64
     Nomber of None Values = 0
            YearOfObservation
      count
                   2147.000000
                   2013.691197
      mean
                      1.385631
       std
                   2012.000000
      min
      25%
                   2012.000000
      50%
                   2013.000000
      75%
                   2015.000000
                   2016.000000
     dtype: float64
# Visualisation
unique_years = df_train['YearOfObservation'].unique()
num_bins = len(unique_years)
# Plot histogram with integer bins
plt.figure(figsize=(12, 6))
sns.histplot(
   x="YearOfObservation",
   data=df train,
   bins=num_bins,
   discrete=True,
   kde=False, # Add a kernel density estimate curve only if it makes sense
   color="skyblue", # Use a light color for better aesthetics
    edgecolor="black" # Add edges for better distinction between bins
# Force x-axis ticks to be integers
plt.xticks(
   ticks=range(df_train['YearOfObservation'].min(), df_train['YearOfObservation'].max() + 1),
    rotation=45 # Rotate x-axis labels for better readability if years are close
plt.title("Distribution of Year of Observation", fontsize=16)
plt.xlabel("Year of Observation", fontsize=14)
plt.ylabel("Frequency", fontsize=14)
plt.grid(axis='y', linestyle='--', alpha=0.7) # Add gridlines for visual clarity
plt.tight_layout() # Ensure layout is not cut off
plt.show()
```

Distribution of Year of Observation



Insured_Period

```
# Analyse
print("Nomber of None Values = ",df_train['Insured_Period'].isna().sum())
display(df_train["Insured_Period"].describe())
print("Nomber of None Values = ",df_test['Insured_Period'].isna().sum())
display(df_test["Insured_Period"].describe())
```

| → | Nomber | of | None | Values | = | 0 |
|----------|--------|----|-------|--------|---|---|
| | | Tr | sured | Period | | |

| | Insured_Period |
|-------|----------------|
| count | 5012.000000 |
| mean | 0.869713 |
| std | 0.219496 |
| min | 0.500000 |
| 25% | 0.500000 |
| 50% | 1.000000 |
| 75% | 1.000000 |
| max | 1.000000 |

dtype: float64

Nomber of None Values = 0

| | Insured_Period |
|-------|----------------|
| count | 2147.000000 |
| mean | 0.876805 |
| std | 0.215504 |
| min | 0.500000 |
| 25% | 1.000000 |
| 50% | 1.000000 |
| 75% | 1.000000 |
| max | 1.000000 |

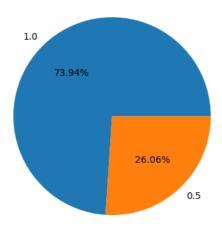
dtype: float64

Visualisation

Insured_Period_counts=df_train['Insured_Period'].value_counts()
labels=list(Insured_Period_counts.index)
df_train['Insured_Period'].value_counts().plot.pie(autopct='%1.2f%%',labels=labels,ylabel="",title='Insured_Period')
plt.show()



Insured_Period



Residential

Analyse

```
print("Nomber of None Values = ",df_train['Residential'].isna().sum())
display(df_train["Residential"].describe())
print("Nomber of None Values = ",df_test['Residential'].isna().sum())
display(df_test["Residential"].describe())
```



| | Residential |
|-------|-------------|
| count | 5012.000000 |
| mean | 0.301077 |
| std | 0.458772 |
| min | 0.000000 |
| 25% | 0.000000 |
| 50% | 0.000000 |
| 75% | 1.000000 |
| max | 1.000000 |

dtype: float64

Nomber of None Values = 0

| | Residential |
|-------|-------------|
| count | 2147.000000 |
| mean | 0.315789 |
| std | 0.464938 |
| min | 0.000000 |
| 25% | 0.000000 |
| 50% | 0.000000 |
| 75% | 1.000000 |
| max | 1.000000 |

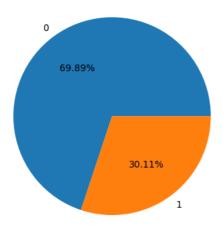
dtype: float64

Visualisation

Residential_counts=df_train['Residential'].value_counts()
labels=list(Residential_counts.index)
df_train['Residential'].value_counts().plot.pie(autopct='%1.2f%%',ylabel="",labels=labels,title='Residential')
plt.show()

 $\overline{\Rightarrow}$

Residential



Building_Painted

Analyse

print("Nomber of None Values = ",df_train['Building_Painted'].isna().sum())
display(df_train["Building_Painted"].describe())
print("Nomber of None Values = ",df_test['Building_Painted'].isna().sum())
display(df_test["Building_Painted"].describe())



Nomber of None Values = 0

| Building Painted | Bui | ldin | g Pa | int | ed |
|------------------|-----|------|------|-----|----|
|------------------|-----|------|------|-----|----|

| | | 0_ | |
|--------|--|----|------|
| count | | | 5012 |
| unique | | | 2 |
| top | | | V |
| freq | | | 3763 |

dtype: object

Nomber of None Values = 0

Building_Painted

| | 0_ |
|--------|------|
| count | 2147 |
| unique | 2 |
| top | V |
| freq | 1619 |

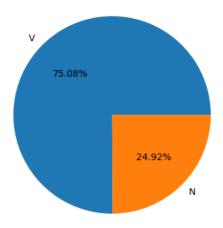
dtype: object

Visualisation

Building_Painted_counts=df_train['Building_Painted'].value_counts() labels=list(Building_Painted_counts.index) df_train['Building_Painted'].value_counts().plot.pie(autopct='%1.2f%%',ylabel="",labels=labels,title='Building_Painted') plt.show()



Building_Painted



Binary Encoding

#(N:oui, V:non)df_train ["Building_Painted"].replace({"N":1,"V":0},inplace=True)
df_test ["Building_Painted"].replace({"N":1,"V":0},inplace=True) #(1 : oui, 0 : non) display(df_train)
display(df_test)

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|---------|-----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 1 | 1 | V | V | U | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | V | V | U | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | N | 0 | R | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | V | V | U | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | V | V | U | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | V | V | U | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | N | 0 | R | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | N | 0 | R | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | N | 0 | R | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | V | V | U | NaN | Wood-framed | without |
| 5012 ro | ws × 11 columns | | | | | | | | |

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|------|----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 0 | 0 | V | V | U | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | N | 0 | R | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | N | 0 | R | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | V | V | U | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | N | 0 | R | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | N | 0 | R | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | V | V | U | NaN | Non- combustible | without |

> Building_Fenced

Analyse

print("Nomber of None Values = ",df_train['Building_Fenced'].isna().sum())
display(df_train["Building_Fenced"].describe())

print("Nomber of None Values = ",df_test['Building_Fenced'].isna().sum())
display(df_test["Building_Fenced"].describe())

Nomber of None Values = 0

| | Building_Fenced |
|--------|-----------------|
| count | 5012 |
| unique | 2 |
| top | N |
| frea | 2535 |

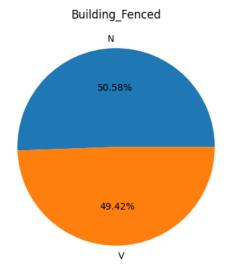
dtype: object
Nomber of None Values = 0

| | Building_Fenced |
|--------|-----------------|
| count | 2147 |
| unique | 2 |
| top | V |
| freq | 1074 |

dtype: object

Building_Fenced_counts=df_train['Building_Fenced'].value_counts() labels=list(Building_Fenced_counts.index) df_train['Building_Fenced'].value_counts().plot.pie(autopct='%1.2f%%',ylabel="",labels=labels,title='Building_Fenced') plt.show()

 $\overline{\Rightarrow}$



Binary Encoding

#(N : oui, V : non)
df_train ["Building_Fenced"].replace({"N":1,"V":0},inplace=True)
df_test ["Building_Fenced"].replace({"N":1,"V":0},inplace=True)

#(1 : oui, 0 : non)
display(df_train) display(df_test)

| | | _ |
|---|---|--------|
| _ | ۵ | \neg |
| | 4 | |

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|---------|-----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 1 | 1 | 0 | V | U | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | 0 | V | U | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | 1 | 0 | R | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | V | U | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | V | U | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | V | U | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | R | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | R | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | R | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | 0 | V | U | NaN | Wood-framed | without |
| 5012 ro | ws x 11 columns | | | | | | | | |

5012 rows × 11 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|------|----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 0 | 0 | 0 | V | U | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | 1 | 0 | R | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | 1 | 0 | R | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | 0 | V | U | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | 1 | 0 | R | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | R | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | 0 | V | U | NaN | Non- combustible | without |

Garden

```
# Analyse
print("Nomber of None Values = ",df_train['Garden'].isna().sum())
display(df_train["Garden"].describe())
print("Nomber of None Values = ",df_test['Garden'].isna().sum())
display(df_test["Garden"].describe())
Nomber of None Values = 4
             Garden
      count
               5008
                  2
      unique
       top
                 0
```

freq

dtype: object
Nomber of None Values = 3

2532

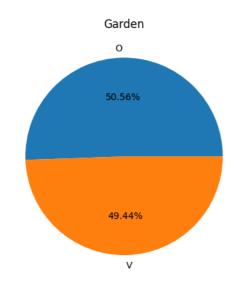
| | Garden |
|--------|--------|
| count | 2144 |
| unique | 2 |
| top | V |
| freq | 1074 |

dtype: object

Visualisation

 $\overline{\Rightarrow}$

Garden_counts=df_train['Garden'].value_counts() labels=list(Garden_counts.index) $\label{linear_def} $$ df_{\tau,i}^{Garden'}.value_counts().plot.pie(autopct='%1.2f\%',ylabel="",labels=labels,title='Garden') $$ df_{\tau,i}^{Garden'}.$$$ plt.show()



Binary Encoding

```
#(V : oui, O : non)
df_train ["Garden"].replace({"V":1,"0":0},inplace=True)
df_test ["Garden"].replace({"V":1,"0":0},inplace=True)
#(1 : oui, 0 : non)
display(df_train)
display(df_test)
```

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|---------|------------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 1 | 1 | 0 | 1.0 | U | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | 0 | 1.0 | U | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | 1 | 0.0 | R | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | 1.0 | U | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | 1.0 | U | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1.0 | U | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | 1 | 0.0 | R | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | 1 | 0.0 | R | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | 1 | 0.0 | R | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | 0 | 1.0 | U | NaN | Wood-framed | without |
| 5012 rc | ows × 11 columns | | | | | | | | |
| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|------|----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 0 | 0 | 0 | 1.0 | U | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | 1 | 0.0 | R | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | 1 | 0.0 | R | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | 0 | 1.0 | U | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | 1 | 0.0 | R | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0.0 | R | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | 0 | 1.0 | U | NaN | Non- combustible | without |

df_train.dropna(subset=["Garden"], inplace=True) display (df_train)

df_test.dropna(subset=["Garden"], inplace=True)
display (df_test)

[#] traitement des valeur manquantes

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|---------|------------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 1 | 1 | 0 | 1.0 | U | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | 0 | 1.0 | U | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | 1 | 0.0 | R | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | 1.0 | U | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | 1.0 | U | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1.0 | U | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | 1 | 0.0 | R | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | 1 | 0.0 | R | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | 1 | 0.0 | R | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | 0 | 1.0 | U | NaN | Wood-framed | without |
| 5008 rc | ows × 11 columns | | | | | | | | |
| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building | Building_Type | NumberOfWindows |

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|------|----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 0 | 0 | 0 | 1.0 | U | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | 1 | 0.0 | R | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | 1 | 0.0 | R | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | 0 | 1.0 | U | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | 1 | 0.0 | R | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0.0 | R | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | 0 | 1.0 | U | NaN | Non- combustible | without |

#Astype

df_train ["Garden"] = df_train["Garden"].astype('int64')
df_test ["Garden"] = df_test["Garden"].astype('int64')

display(df_train)
display(df_test)

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | Settlement | Building Dimension | Building_Type | NumberOfWindows |
|---------|-----------------|-------------|------------------|-----------------|--------|------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | U | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | 0 | 1 | U | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | 1 | 0 | R | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | 1 | U | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | 1 | U | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | U | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | R | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | R | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | R | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | U | NaN | Wood-framed | without |
| 5008 ro | ws × 11 columns | | | | | | | | |

| NumberOfWindows | Building_Type | Building Dimension | Settlement | Garden | Building_Fenced | Building_Painted | Residential | Insured_Period | |
|-----------------|---------------------|-----------------------|------------|--------|-----------------|------------------|-------------|----------------|------|
| without | Fire-resistive | 3760.0 | U | 1 | 0 | 0 | 0 | 1.0 | 0 |
| 5 | Fire-resistive | 1452.0 | R | 0 | 1 | 0 | 0 | 1.0 | 1 |
| 6 | Ordinary | 1944.0 | R | 0 | 1 | 0 | 1 | 1.0 | 2 |
| without | Non- combustible | 2270.0 | U | 1 | 0 | 1 | 0 | 1.0 | 3 |
| 9 | Fire-resistive | 2976.0 | R | 0 | 1 | 0 | 0 | 0.5 | 4 |
| | | | | | | | | | |
| 2 | Wood-framed | 862.0 | R | 0 | 1 | 0 | 1 | 0.5 | 2142 |
| without | Non- combustible | NaN | U | 1 | 0 | 0 | 0 | 1.0 | 2143 |

> Settlement (urbain_zone)

Analyse

print("Nomber of None Values = ",df_train['Settlement'].isna().sum()) display (df_train["Settlement"].describe())

print("Nomber of None Values = ",df_test['Settlement'].isna().sum()) display (df_test["Settlement"].describe())

Nomber of None Values = 0

Settlement 5008 count unique 2 R top freq 2533

dtype: object
Nomber of None Values = 0

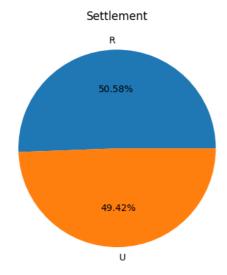
Settlement 2144 count unique U top 1074 freq

dtype: object

Visualisation

labels=list(Settlement_counts.index)
df_train['Settlement'].value_counts().plot.pie(autopct='%1.2f%%',ylabel="",labels=labels,title='Settlement')
plt.show()

 \overline{z}



Binary Encoding

#(R : zone rurale, U : zone urbain)
df_train ["Settlement"].replace({"U":1,"R":0},inplace=True)
df_test ["Settlement"].replace({"U":1,"R":0},inplace=True)
#(1 : zone urbain , 0 : zone rurale)
df_train = df_train.rename(columns={'Settlement': 'urbain_zone'})
df_test = df_test.rename(columns={'Settlement': 'urbain_zone'})
display(df_train)
display(df_test)

| <u> </u> | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Building Dimension | Building_Type | NumberOfWindows |
|----------|----------------|-------------|------------------|-----------------|--------|-------------|-----------------------|---------------------|-----------------|
| (| 1.0 | 1 | 1 | 0 | 1 | 1 | 1240.0 | Wood-framed | without |
| , | 1.0 | 0 | 1 | 0 | 1 | 1 | 900.0 | Non- combustible | without |
| 2 | 2 1.0 | 1 | 0 | 1 | 0 | 0 | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 50 | 07 1.0 | 0 | 1 | 0 | 1 | 1 | 550.0 | Ordinary | without |
| 50 | 08 0.5 | 0 | 0 | 1 | 0 | 0 | 1000.0 | Fire-resistive | 4 |
| 50 | 09 1.0 | 1 | 0 | 1 | 0 | 0 | 480.0 | Ordinary | 3 |
| 50 | 10 0.5 | 0 | 0 | 1 | 0 | 0 | 536.0 | Fire-resistive | 4 |
| 50 | 11 1.0 | 1 | 0 | 0 | 1 | 1 | NaN | Wood-framed | without |

5008 rows × 11 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Building Dimension | Building_Type | NumberOfWindows |
|------|----------------|-------------|------------------|-----------------|--------|-------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | NaN | Non- combustible | without |

h. 1

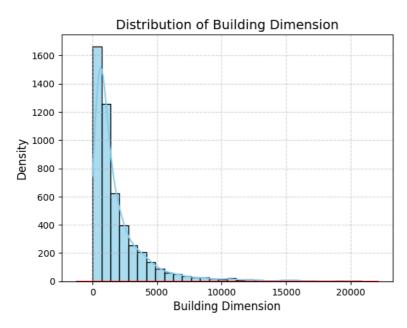
Building Dimension

plt.ylabel("Density", fontsize=12)

plt.show()

plt.grid(visible=True, linestyle='--', alpha=0.5)

```
# Analyse
print("Nomber of None Values = ",df_train['Building Dimension'].isna().sum())
display (df_train["Building Dimension"].describe())
print("Nomber of None Values = ",df_test['Building Dimension'].isna().sum())
display (df_test["Building Dimension"].describe())
Nomber of None Values = 77
            Building Dimension
                    4931.000000
      count
                    1876.147232
      mean
                    2267.016703
       std
                       1.000000
      min
                     520.000000
      25%
      50%
                    1067.000000
      75%
                    2280.000000
                   20840.000000
      max
     dtype: float64
     Nomber of None Values = 29
            Building Dimension
                    2115.000000
     count
      mean
                    1896.437352
                    2301.002647
       std
      min
                      10.000000
      25%
                     536.000000
      50%
                    1100.000000
      75%
                    2296.000000
                   20940.000000
      max
     dtype: float64
# Visualisation
sns.histplot(df_train['Building Dimension'], kde=True, bins=30, color='skyblue', edgecolor='black', alpha=0.7)
sns.kdeplot(df_train['Building Dimension'], bw_method='scott', bw_adjust=1, color='red', linewidth=2)
plt.title("Distribution of Building Dimension", fontsize=14)
plt.xlabel("Building Dimension", fontsize=12)
```



traitement des valeur manquantes

 $\label{eq:df_train} \mbox{ = traitement_des_valeurs_manquantes(df_train,'Building Dimension') } \\ \mbox{ display (df_train)}$

df_test = traitement_des_valeurs_manquantes(df_test,'Building Dimension')
display (df_test)

| → | | | | | | | Building | | |
|----------|------------------|-------------|------------------|-----------------|--------|-------------|-----------------------|---------------------|-----------------|
| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Dimension | Building_Type | NumberOfWindows |
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 4984.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 400.0 | Wood-framed | without |
| 5008 rd | ows × 11 columns | | | | | | | | |
| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Building Dimension | Building_Type | NumberOfWindows |
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 400.0 | Non- combustible | without |
| | | | | | | | | | |

outliers

df_train=treatment_des_outliers(df_train, "Building Dimension")
display (df_train)

| 3 | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Building Dimension | Building_Type | NumberOfWindows |
|---------|------------------|-------------|------------------|-----------------|--------|-------------|-----------------------|---------------------|-----------------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1240.0 | Wood-framed | without |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 900.0 | Non- combustible | without |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 4875.0 | Non- combustible | 4 |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 600.0 | Wood-framed | without |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 900.0 | Non- combustible | without |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 550.0 | Ordinary | without |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1000.0 | Fire-resistive | 4 |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 480.0 | Ordinary | 3 |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 536.0 | Fire-resistive | 4 |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 400.0 | Wood-framed | without |
| 5008 rd | ows × 11 columns | | | | | | | | |
| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Building Dimension | Building_Type | NumberOfWindows |
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 3760.0 | Fire-resistive | without |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 1452.0 | Fire-resistive | 5 |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1944.0 | Ordinary | 6 |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 2270.0 | Non- combustible | without |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 2976.0 | Fire-resistive | 9 |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 862.0 | Wood-framed | 2 |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 400.0 | Non- combustible | without |

Verification

```
print("Nomber of None Values = ",df_train['Building Dimension'].isna().sum())
display (df_train["Building Dimension"].describe())
print("Nomber of None Values = ",df_test['Building Dimension'].isna().sum())
display (df_test["Building Dimension"].describe())

sns.histplot(df_train['Building Dimension'], kde=True, bins=30, color='skyblue', edgecolor='black', alpha=0.7)
sns.kdeplot(df_train['Building Dimension'], bw_method='scott', bw_adjust=1, color='red', linewidth=2)
plt.title("Distribution of Building Dimension", fontsize=14)
plt.xlabel("Building Dimension", fontsize=12)
plt.ylabel("Density", fontsize=12)
plt.grid(visible=True, linestyle='--', alpha=0.5)
plt.show()
```

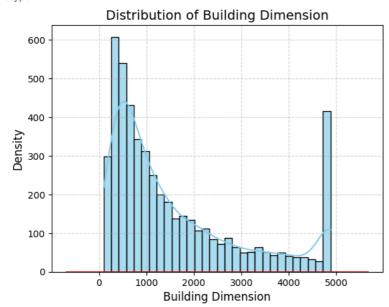
 \rightarrow Nomber of None Values = 0 **Building Dimension**

| | O . |
|-------|-------------|
| count | 5008.000000 |
| mean | 1611.475040 |
| std | 1428.627826 |
| min | 101.000000 |
| 25% | 500.000000 |
| 50% | 1037.500000 |
| 75% | 2250.000000 |
| max | 4875.000000 |

dtype: float64
Nomber of None Values = 0

| | Building Dimension |
|-------|--------------------|
| count | 2144.000000 |
| mean | 1630.354594 |
| std | 1426.733205 |
| min | 110.000000 |
| 25% | 514.500000 |
| 50% | 1069.000000 |
| 75% | 2263.250000 |
| max | 4886.375000 |

dtype: float64



```
# Binary Encoding
```

```
\#Summary of the central tendency, dispersion, and shape of a dataset's distribution.
print(df_train["Building Dimension"].describe())
#The 33th percentile (first Tertiles)
Q1 = df_train['Building Dimension'].quantile(0.33)
#The 66th percentile (Second Tertiles)
Q2 = df_train['Building Dimension'].quantile(0.66)
print (Q1,Q2)
df_train["Small_Building"]=np.where(df_train['Building Dimension']<=Q1 , 1 , 0)</pre>
\label{lem:df_train["Medium_Building"]=np.where((df_train['Building Dimension']>=Q1 )&(df_train['Building Dimension']<=Q2), 1 , 0) \\
\label{linear_def} $$ df_{\tau}["Large_Building"]=np.where(df_{\tau}['Building_Dimension']>=Q2\ ,\ 1\ ,\ 0)$
df_train=df_train.iloc[:, [0,1,2,3,4,5,11,12,13,7,8,9,10,]]
display (df_train)
df_test["Small_Building"]=np.where(df_test['Building Dimension']<=Q1 , 1 , 0)</pre>
df_test["Medium_Building"]=np.where((df_test['Building Dimension']>=Q1 )&(df_test['Building Dimension']<=Q2), 1 , 0)</pre>
df_test["Large_Building"]=np.where(df_test['Building Dimension']>=Q2 , 1 , 0)
df_test=df_test.iloc[:, [0,1,2,3,4,5,11,12,13,7,8,9,10,]]
display (df_test)
```

→ count 5008.000000 mean 1611.475040 std 1428.627826 min 101.000000 25% 500.000000 1037.500000 50% 75% 2250.000000 4875.000000 max

Name: Building Dimension, dtype: float64

650.0 1699.2400000000007

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|---------------------------|--|------------------|--------------------|---------------------------|-----------------------|---------------------------|-------------------|------------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | ••• | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |
| E000 == | ows × 13 columns | | | | | | | | |
| 2000 10 | JW3 ^ 10 COIGITIII3 | | | | | | | | |
| 500610 | | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
| 0 | | Residential 0 | Building_Painted 0 | Building_Fenced 0 | Garden | urbain_zone | Small_Building 0 | Medium_Building | Large_Bu |
| | Insured_Period | | | | | | | | Large_Bu |
| 0 | Insured_Period | 0 | 0 | 0 | 1 | 1 | 0 | 0 | Large_Bu |
| 0 | Insured_Period 1.0 1.0 | 0 | 0 | 0 | 1 0 | 1 0 | 0 | 0 | Large_Bu |
| 0 1 2 | 1.0 1.0 1.0 | 0 0 1 | 0 0 | 0 1 1 | 1 0 0 | 1 0 0 | 0 0 | 0 1 0 | Large_Bu |
| 0 1 2 3 | 1.0 1.0 1.0 1.0 | 0 0 1 | 0 0 0 1 | 0 1 1 | 1 0 0 | 1 0 0 | 0 0 0 | 0 1 0 | Large_Bu |
| 0 1 2 3 | 1.0 1.0 1.0 1.0 1.0 | 0 0 1 0 | 0 0 0 1 | 0 1 1 0 | 1 0 0 1 | 1 0 0 1 | 0 0 0 0 | 0 1 0 0 | Large_Bu |
| 0 1 2 3 4 | 1.0 1.0 1.0 1.0 1.0 0.5 | 0 0 1 0 | 0 0 1 0 | 0 1 1 0 1 | 1 0 0 1 0 | 1 0 0 1 0 | 0 0 0 0 | 0 1 0 0 | Large_Bu |
| 0 1 2 3 4 | 1.0 1.0 1.0 1.0 1.0 0.5 | 0 0 1 0 1 | 0 0 1 0 0 | 0 1 1 0 1 | 1 0 0 1 0 0 | 1 0 0 1 0 | 0 0 0 0 0 | 0 1 0 0 1 | Large_Bu |

0

1

2144 rows × 13 columns

Building_Type

2146

```
# Analyse
```

print("Nomber of None Values = ",df_train['Building_Type'].isna().sum())
display (df_train["Building_Type"].describe())

0

print("Nomber of None Values = ",df_test['Building_Type'].isna().sum())
display (df_test["Building_Type"].describe())

| ₹ | Nomber o | of None Values = Building_Type | 0 |
|---|-----------------------|--------------------------------------|---|
| | count | 5008 | |
| | unique | 4 | |
| | top | Non-combustible | |
| | freq | 2310 | |
| | dtype: ob Nomber o | oject of None Values = Building_Type | 0 |
| | count | 2144 | |
| | unique | 4 | |

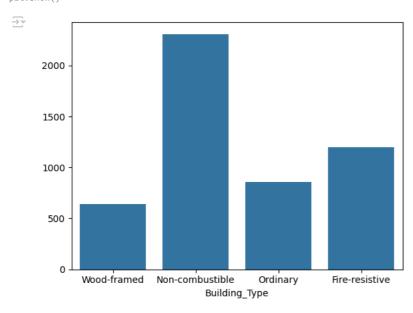
dtype: object

top freq

Visualisation

sns.countplot(x="Building_Type", data=df_train)
plt.ylabel("")
plt.show()

Non-combustible



Binary Encoding

df_train=pd.get_dummies(df_train, columns=["Building_Type"],prefix="Building_Type", prefix_sep="_", dtype="int64")
df_train=df_train.iloc[:, [0,1,2,3,4,5,6,7,8,12,13,14,15,9,10,11]]
display (df_train)

 $df_test=pd.get_dummies(df_test, columns=["Building_Type"], prefix="Building_Type", prefix_sep="_", dtype="int64") \\ df_test=df_test.iloc[:, [0,1,2,3,4,5,6,7,8,12,13,14,15,9,10,11]] \\ display (df_test)$

| | | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|----|-----|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| | 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| ; | 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| | 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | | |
| 50 | 007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 50 | 800 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 50 | 009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 50 |)10 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 50 |)11 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |
| | | | | | | | | | | |

5008 rows × 16 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2144 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2145 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2146 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2144 rows × 16 columns

V NumberOfWindows

Analyse

print("Nomber of None Values = ",df_train['NumberOfWindows'].isna().sum()) display(df_train["NumberOfWindows"].describe())

print("Nomber of None Values = ",df_test['NumberOfWindows'].isna().sum()) display(df_test["NumberOfWindows"].describe())

Nomber of None Values = 0

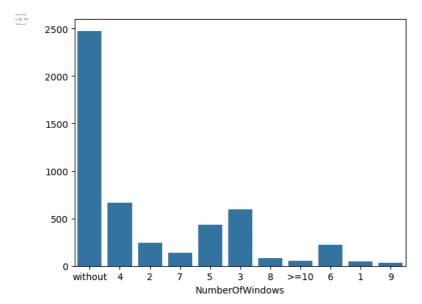
| | NumberOfWindows |
|--------|-----------------|
| count | 5008 |
| unique | 11 |
| top | without |
| freq | 2476 |

dtype: object
Nomber of None Values = 0

| | NumberOfWindows |
|--------|-----------------|
| count | 2144 |
| unique | 11 |
| top | without |
| freq | 1074 |

dtype: object

```
sns.countplot(x="NumberOfWindows", data=df_train)
plt.ylabel("")
plt.show()
```



Outliers

 $\label{lem:condition} $$ df_{\tau}("\norm{\color{loop}{\color{\color{loop}{\color{loop}{\color{loop}{\color{loop}{\color{lo$

| - | -> | -41 |
|---|----|-----|
| | | |

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

5008 rows × 16 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2144 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2145 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2146 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2144 rows × 16 columns

```
# Binary Encoding
```

```
#(without dans le cas de 0 fenêtre)
df_train["NumberOfWindows"].replace({"without":0},inplace=True)
df_train['NumberOfWindows'] = pd.to_numeric(df_train['NumberOfWindows']).astype('int64')
#(0 dans le cas de 0 fenêtre)
display (df_train)

#(without dans le cas de 0 fenêtre)
df_test["NumberOfWindows"].replace({"without":0},inplace=True)
df_test['NumberOfWindows'] = pd.to_numeric(df_test['NumberOfWindows']).astype('int64')
#(0 dans le cas de 0 fenêtre)
display (df_test)
```

| | | _ |
|---|----|-----|
| - | -> | -71 |
| | | |

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

5008 rows × 16 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2144 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2145 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2146 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2144 rows × 16 columns

verification

print("Nomber of None Values = ",df_train['NumberOfWindows'].isna().sum())
display(df_train["NumberOfWindows"].describe())
print("Nomber of None Values = ",df_test['NumberOfWindows'].isna().sum())
display(df_test["NumberOfWindows"].describe())

 $\label{lem:countplot} $$sns.countplot(x="NumberOfWindows", data=df_train) $$plt.ylabel("") $$plt.show() $$$

Nomber of None Values = 0

| | NumberOfWindows |
|-------|-----------------|
| count | 5008.000000 |
| mean | 2.202676 |
| std | 2.535834 |
| min | 0.000000 |
| 25% | 0.000000 |
| 50% | 1.000000 |
| 75% | 4.000000 |
| | |

dtype: float64

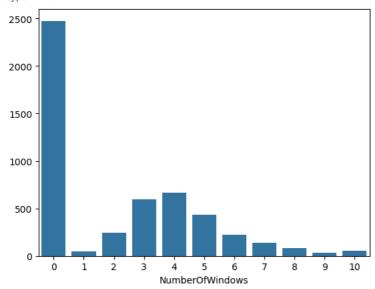
max

Nomber of None Values = 0

10.000000

| | NumberOfWindows |
|-------|-----------------|
| count | 2144.000000 |
| mean | 2.134795 |
| std | 2.480540 |
| min | 0.000000 |
| 25% | 0.000000 |
| 50% | 0.000000 |
| 75% | 4.000000 |
| max | 10.000000 |





Geo_Code

Analyse

print("Nomber of None Values = ",df_train['Geo_Code'].isna().sum()) display(df_train["Geo_Code"].describe())

print("Nomber of None Values = ",df_test['Geo_Code'].isna().sum()) display(df_test["Geo_Code"].describe())

| | Geo_Code |
|--------|----------|
| count | 4935 |
| unique | 1115 |
| top | 6088 |
| frea | 102 |

dtype: object
Nomber of None Values = 29

| | Geo_Code |
|--------|----------|
| count | 2115 |
| unique | 713 |
| top | 6088 |
| freq | 41 |

dtype: object

Visualisation

Remove Nan values

#most_frequent
df_train['Geo_Code'].ffill(inplace=True)
display(df_train)

df_test['Geo_Code'].ffill(inplace=True)
display(df_test)

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

5008 rows × 16 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2144 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2145 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2146 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2144 rows × 16 columns

```
PR 606
                   47.3
        PR 610
4
                  264.4
        PR 911
101
                 6028.4
102
        PR 912
                 6474.9
103
        PR 913
                 7984.8
104
        PR 915
                 6743.9
        PR 917
```

[100 rows x 3 columns]

Creation d'une DF Extern

```
state_density_df = zipcode_data.groupby('state_id').agg(
    zip_start=('zip', 'min'),
    zip_end=('zip', 'max'),
    new_density=('density', 'mean')
).reset_index()
state_density_df = state_density_df.sort_values(by='zip_start').reset_index(drop=True)
print(state_density_df)
```

```
state_id zip_start zip_end new_density
0 PR 601 987 1105.897710
```

```
МΔ
                        1001
                                 2791 1218,233581
     2
              RT
                        2802
                                 2921 1148.051852
     3
              NH
                        3031
                                 3897
                                         123.766802
                        3901
                                 4992
                                          67.660798
                        5001
                                 5907
                                          90.939623
     6
              СТ
                        6001
                                 6907
                                         646.406597
                        6390
                                14905
                                        2141.604605
              NY
                                       1532.152843
     8
              NJ
                        7001
                                 8904
                                19611
     9
              PΑ
                       15001
                                         533,255950
     10
              DE
                       19701
                                19980
                                         564,182353
     11
              DC
                       20001
                                20591
                                        3083, 259649
     12
              VΔ
                       20105
                                24657
                                         378.867996
     13
              MD
                       20601
                                21930
                                         617.602516
                       24701
                                26886
                                          76.365718
     15
                       27006
                                28909
                                         240.443611
                       29001
                                29945
                                         264.124292
     17
              GΑ
                       30002
                                39897
                                         320.006933
                                34997
     18
              FL
                       32003
                                         831.325519
     19
              ΑL
                       35004
                                36925
                                         190.644512
     20
              TN
                       37010
                                38589
                                         208.791667
     21
              MS
                       38601
                                39776
                                         94.829508
     22
              ΚY
                       40003
                                42788
                                         161.256923
     23
              ОН
                       43001
                                45899
                                         374.595377
     24
              IN
                       46001
                                47997
                                         255.988971
     25
                       48001
                                49971
                                         320.228730
     26
                                52807
                       50001
                                         84.372062
     27
                       53001
                                54986
                                         231.827075
     28
                       55001
                                56763
              MN
                                         249.419410
     29
              SD
                       57001
                                57799
                                          39.168800
     30
                       58001
                                58856
                                          52.396649
              ND
                       59001
                                59937
                                          28.575068
     31
              MT
     32
              IL
                       60002
                                62999
                                         544.584670
     33
              MO
                       63005
                                65897
                                         181.357874
     34
              KS
                       66002
                                67954
                                         111.032244
     35
              NE
                       68001
                                69367
                                         126.082765
     36
                       70001
                                71497
                                         304.879406
                                72959
     37
                       71601
                                         82.302602
     38
              ОК
                       73001
                                74966
                                         140.720934
     39
                       73960
                                79938
                                         466.607387
              TX
     40
                       80002
                                81657
                                         434.536243
     41
                                83414
                                         12.277654
              WY
                       82001
     42
              ID
                       83201
                                83876
                                         98.133692
     43
              UT
                       84001
                                84790
                                         298.337584
     44
              Δ7
                       85003
                                86556
                                         517.472662
     45
              MM
                       87001
                                88439
                                         107.021024
     46
              NV
                       89001
                                89883
                                         655.026257
     47
                       90001
                                96161
                                        1306.829079
     48
              ΗI
                       96701
                                96863
                                         727.492784
     49
                       97001
                                97920
                                         316.825761
                                99403
     50
              WA
                       98001
                                         600.268595
                       99501
                                99929
     51
              ΑK
                                         63.368980
# Creation des nouveaux Features
# Function to find state and density
def find_state_density(geo_code, state_density_df):
    if pd.isna(geo_code):
        return pd.Series([None, None]) # Return None for missing Geo_Code
    # Ensure the Geo_Code is numeric
        geo_code = int(geo_code)
    except ValueError:
        # Return None if Geo_Code is not numeric
        return pd.Series([None, None])
    # Filter the dataframe to find the matching row
    row = state_density_df[
        (state_density_df['zip_start'] <= geo_code) &</pre>
        (state_density_df['zip_end'] >= geo_code)
    if not row.empty:
        return pd.Series([row.iloc[0]['state_id'], row.iloc[0]['new_density']])
    else:
        return pd.Series([None, None])
if 'Geo_Code' in df_train.columns:
  # Apply the function to each Geo_Code
  df_train[['State', 'City_Density']] = df_train['Geo_Code'].apply(
      lambda x: find_state_density(x, state_density_df)
if 'Geo_Code' in df_test.columns:
  # Apply the function to each Geo_Code
  df_test[['State', 'City_Density']] = df_test['Geo_Code'].apply(
      lambda x: find_state_density(x, state_density_df)
```

display (df_train)
display (df_test)

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

5008 rows × 17 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2144 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2145 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2146 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2144 rows × 17 columns

#ordre des colunm

df_train=df_train.iloc[:, [0,1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,14]]
display (df_train)
df_test=df_test.iloc[:, [0,1,2,3,4,5,6,7,8,9,10,11,12,13,15,16,14]]
display (df_test)

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 5007 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 5008 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 5009 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5010 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 5011 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

5008 rows × 17 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2142 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2143 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2144 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2145 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2146 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2144 rows × 17 columns

State

Analyse

print("Nomber of None Values = ",df_train['State'].isna().sum()) display(df_train["State"].describe())

print("Nomber of None Values = ",df_test['State'].isna().sum()) display (df_test["State"].describe())

Nomber of None Values = 65

| | State |
|--------|-------|
| count | 4943 |
| unique | 37 |
| top | NY |
| freq | 705 |

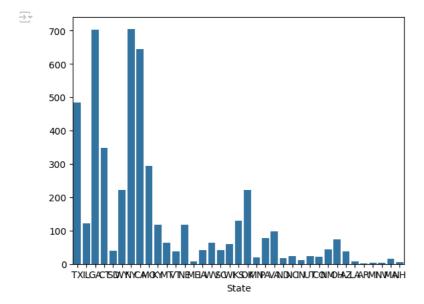
dtype: object
Nomber of None Values = 37

| | State |
|--------|-------|
| count | 2107 |
| unique | 37 |
| top | NY |
| freq | 336 |

dtype: object

Visualisation

```
sns.countplot(x="State", data=df_train)
plt.ylabel("")
plt.show()
```



traitement des valeur manquantes

 $\label{train.dropna} $$ df_{\text{train.dropna}}(subset=["State"],axis=0 , inplace=True,ignore_index=True) $$ display (df_{\text{train}}) $$$

 $\label{linear_def} $$ df_{\text{test.dropna}(\text{subset=["State"],axis=0 , inplace=True,ignore_index=True)} $$ display (df_{\text{test}}) $$$

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 4938 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4939 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 4940 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 4941 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 4942 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

4943 rows × 17 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2102 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2103 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2104 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2105 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2106 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2107 rows × 17 columns

```
# Label Encoading State
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df_train['State'] = encoder.fit_transform(df_train['State'])
df_test['State'] = encoder.fit_transform(df_test['State'])
```

City_Density

```
# Analyse
print("Nomber of None Values = ",df_train['City_Density'].isna().sum())
display(df_train["City_Density"].describe())
print("Nomber of None Values = ",df_test['City_Density'].isna().sum())
display (df_test["City_Density"].describe())
```

→ Nomber of None Values = 0

| | City_Density |
|-------|--------------|
| count | 4943.000000 |
| mean | 699.039490 |
| std | 696.478626 |
| min | 12.277654 |
| 25% | 181.357874 |
| 50% | 378.867996 |
| 75% | 1306.829079 |
| max | 2141.604605 |

dtype: float64

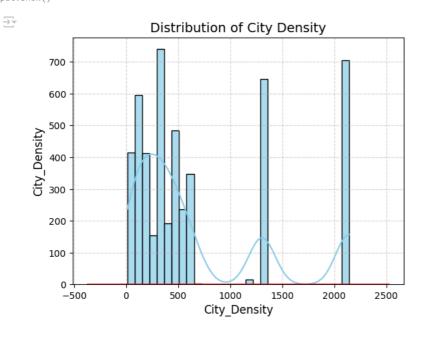
Nomber of None Values = 0

| | City_Density |
|-------|--------------|
| count | 2107.000000 |
| mean | 731.164610 |
| std | 721.551011 |
| min | 12.277654 |
| 25% | 181.357874 |
| 50% | 466.607387 |
| 75% | 1306.829079 |
| max | 2141.604605 |

dtype: float64

Visualisation

```
sns.histplot(df_train["City_Density"], kde=True, bins=30, color='skyblue', edgecolor='black', alpha=0.7)
sns.kdeplot(df_train["City_Density"], bw_method='scott', bw_adjust=1, color='red', linewidth=2)
plt.title("Distribution of City Density", fontsize=14)
plt.xlabel("City_Density", fontsize=12)
plt.ylabel("City_Density", fontsize=12)
plt.grid(visible=True, linestyle='--', alpha=0.5)
plt.show()
```



#Astype

```
df_train ["City_Density"] = df_train["City_Density"].astype(int)
df_test ["City_Density"] = df_test["City_Density"].astype(int)
```

display(df_train)
display(df_test)

| | _ |
|--|---|

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | |
| 4938 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4939 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 4940 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 4941 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 4942 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |

4943 rows × 17 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2102 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2103 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2104 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2105 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2106 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2107 rows × 17 columns

Claim

Analyse

print("Nomber of None Values = ",df_train['Claim'].isna().sum()) display(df_train["Claim"].describe())

print("Nomber of None Values = ",df_test['Claim'].isna().sum()) display(df_test["Claim"].describe())

Nomber of None Values = 0

4943 unique 2 top non freq 3837

dtype: object
Nomber of None Values = 0

Claim 2107 count 2 unique top non freq 1608

dtype: object

```
# Visualisation
Claim_counts=df_train['Claim'].value_counts()
labels=list(Claim_counts.index)
df_train['Claim'].value_counts().plot.pie(autopct='%1.2f%%',ylabel="",labels=labels,title='Claim')
plt.show()
```



77.62% 22.38%

Claim

Binary Encoding

```
#(oui : Claim , non : Not Claim)
df_train ["Claim"].replace({"oui":1,"non":0},inplace=True)
df_test ["Claim"].replace({"oui":1,"non":0},inplace=True)
#(1 : Claim , 0 : Not Claim)
display(df_train)
display(df_test)
```

| | | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|----|----|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| (| 0 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| , | 1 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 2 | 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| ; | 3 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4 | 4 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |
| | | | | | | | | | | |
| 49 | 38 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 49 | 39 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 49 | 40 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 49 | 41 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 49 | 42 | 1.0 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | |
| | | | | | | | | | | |

4943 rows × 17 columns

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 0 | 1.0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | |
| 1 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2 | 1.0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | |
| 3 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |
| 4 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | |
| | | | | | | | | | |
| 2102 | 0.5 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2103 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 2104 | 1.0 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 2105 | 1.0 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 2106 | 0.5 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | |

2107 rows × 17 columns

Label Encoading State
from sklearn.preprocessing import LabelEncoder
encoder = LabelEncoder()
df_train['State'] = encoder.fit_transform(df_train['State'])
df_test['State'] = encoder.fit_transform(df_test['State'])

Data Preprocessing (More Treatement)

Traitement des duplicata (lignes)
duplicated_df_train = df_train[df_train.duplicated()]
display(duplicated_df_train)

duplicated_df_test = df_test[df_test.duplicated()]
display (duplicated_df_test)

| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
|------------------------|----------------|-------------|------------------|-----------------|--------|-------------|----------------|-----------------|----------|
| 58 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 87 | 1.0 | 0 | 0 | 0 | 1 | 1 | 1 | 0 | |
| 91 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 103 | 1.0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | |
| 127 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| | | | | | | | | | |
| 4937 | 0.5 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4938 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 4939 | 0.5 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | |
| 4940 | 1.0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 4941 | 0.5 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | |
| 2819 rows × 17 columns | | | | | | | | | |
| | Insured_Period | Residential | Building_Painted | Building_Fenced | Garden | urbain_zone | Small_Building | Medium_Building | Large_Bu |
| 51 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 58 | 1.0 | 0 | 1 | 0 | 1 | 1 | 1 | 0 | |
| 59 | 1.0 | 0 | 1 | 0 | 1 | 1 | 0 | 0 | |

df_train.drop_duplicates(inplace=True, ignore_index=True)
df_test.drop_duplicates(inplace=True, ignore_index=True)